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ESTIMATION OF REVEALED PROBABILITIES AND UTILITY FUNCTIONS FOR PRODUCT SAFETY DECISIONS

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Abstract—Using survey data on consumer product purchases, this paper introduces an approach to estimate jointly individual utility functions and risk perceptions implied by their decisions. The behavioral risk beliefs reflected in consumers' risky decisions differ from the stated probabilities given to them in the survey. These results are not consistent with a Bayesian learning model in which the information respondents utilize is restricted to what the survey presents. The results are, however, potentially consistent with models in which prior risk information is influential or models in which people do not act in a fully rational manner.

I. Introduction

A FUNDAMENTAL concern in decision analysis and the economics of risk and uncertainty is the structure of individual utility functions. This prominence, in turn, has led to the development of procedures to estimate the structure of utility functions. Perhaps the most widely used approach is to present individuals with a series of hypothetical examples, ascertain their responses, and estimate the utility function implied by this behavior.[1] This technique presupposes, however, that individuals view the probabilistic information presented to them as being fully informative.

The nature of utility functions and the rationality of preferences more generally have also been the focus of a large literature on choice under uncertainty. A wide range of studies has documented a variety of forms of irrationality and systematic errors in uncertain decisions.[2] Most of this literature is based on various kinds of experimental evidence in which respondents consider a series of hypothetical lotteries, which is a methodological approach not too dissimilar from the use of reference lotteries to determine individual utility functions.[3] In each case the analysis is based on an assumption that individuals treat probabilistic information at face value and process it accurately. Under these assumptions, information on subsequent decisions provides evidence on the structure of individual preferences.

The assumption that probabilistic information is processed accurately and treated as being fully informative may not, however, be accurate. This paper extends the analysis in Evans and Viscusi (1991) by introducing a new econometric procedure for simultaneously estimating the probabilities implicit in uncertain choices and the utility functions revealed by these decisions. The primary benefit of our technique is that it does not treat the probabilistic information at face value. The primary contribution of this paper is methodological in that it introduces what, to the best of our knowledge, is the first approach to jointly estimating preferences and risk perceptions. We also will derive insights for consumer risk. As we illustrate below, our results are potentially consistent both with broadly defined Bayesian models and with the literature on irrational choice. The estimation illuminates the specific aspects of perceptional relationships that generate the departure from a perfect information reference point.

Section II develops an empirical model for a consumer product survey examined in this review by Evans and Viscusi (1991) in which respondents were told the risk associated with various consumer products. We then develop a structural model that tests whether these probabilities are taken at face value or whether individuals incorporate the stated probabilities within the context of a Bayesian learning process.[4] The empirical results reported in section III simultaneously estimate both the risk perceptions revealed through individual decisions as well as the structure of utility functions, thus eliminating the distorting effect of perceptional biases. The revealed probabilities exhibit a pattern that we term the "probability compression effect." High probabilities are muted, and low probabilities are raised.

II. Modeling of Behavioral Probabilities for Consumer Choice

The survey used in the Evans and Viscusi (1991) study that will be examined here involves probabilities stated in the survey. This approach is the norm for experimental studies that present individuals with hypothetical lotteries and elicit choices among them. We will focus on how these stated probabilities correspond to the probabilities people assess after receiving this information. The estimation approach presented below explicitly explores the risk beliefs implicit in consumer choices.

To examine the role of perceptional biases, we will use a large set of consumer survey data dealing with the risks posed by two household chemical products—toilet bowl cleaner and insecticide. These data sets are based on the price responses of several hundred representative consumers to different possible formulations of these household chemicals.[5] Each product involved a pair of nonfatal risks $j = 1, 2,$

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[1] See Keeney and Raiffa (1976) and Kleindorfer et al. (1993) for a lucid overview of this work.

[2] See, among others, Combs and Slovic (1974), Fischhoff et al. (1981), Kahneman and Tversky (1979), Kunreuther et al. (1978), Lichtenstein et al. (1978), Machina (1987), Viscusi (1992), and Kleindorfer et al. (1993).

[3] See Raiffa (1968) for a discussion of this approach.

[4] For a review, see Kahneman and Tversky (1979), Fischhoff et al. (1981), Viscusi (1992), and Kleindorfer et al. (1993).

[5] These original data sets were developed by the senior author of this paper in research he directed for the U.S. Environmental Protection Agency. The sample characteristics are reported in Viscusi et al. (1987) and Magat and Viscusi (1992, chap. 2). The latter publication also reports telephone survey results on actual product usage as a validity test of the relationship between the survey responses and actual consumer behavior. The adult consumer samples used focus on the household chemical risks to adults, not the smaller samples involving risks to children. There were 508 observations in the toilet bowl cleaner sample and 607 in the insecticide

TABLE 1.—SUMMARY OF CONSUMER PRODUCT SAFETY EXPERIMENTAL TREATMENTS

Survey Question	Baseline Risk per 10,000 Bottles		New Product Risk per 10,000 Bottles	
	p_1	p_2	s_1	s_2
1	15	15	0	15
2	15	15	15	0
3	15	15	0	0
4	15	15	10	10
5	15	15	5	5

which were gassings and eyeburns for toilet bowl cleaner and inhalations and skin poisonings for insecticide.

The survey informed respondents that the per-bottle baseline risk value p_j was 15/10,000 for each of the two risks of the products. The survey then inquired about the respondent's view of some safer variants of the product posing risks s_j for each of the two risks. Table 1 summarizes the five different ways in which the baseline risks were altered. These experimental treatments were the same for both products. Each respondent considered all five treatments for only one of the products listed in table 1. The value of s_j varies from 0 to 15/10,000.[6]

It is usually assumed in studies such as this that respondents treat the value of s_j as representing the risks of the product. If this is the case, then in effect the respondent's prior risk assessment is given a zero informational weight, whereas there is an infinite relative weight on the survey value of s_j in forming the respondent's assessment of the risk, which we denote by q_j. In his prospective reference theory model, Viscusi (1989, 1992) hypothesized that respondents may not take the s_j amounts at face value but instead may treat this amount as providing partial information in a quasi-Bayesian context.

Two possibilities will be considered. In case 1 we test whether individuals restrict their information to what they are told in the survey, including both the initial baseline risk and new risk information for the reformulated product. In case 2 we test whether respondents augment information presented in the survey with their own risk beliefs so that risk assessments based on prior knowledge, initial risk information, and new product risk information may all be consequential.

Consider first the learning process for case 1. The notation used is as follows. Let the value of p_j be the prior risk assessment, and s_j the risk implied by new information. Suppose that respondents attached some precision γ to the baseline risks p_j, where γ is equivalent to the number of draws from an urn that this information represents. We assume that probabilities can be characterized using a beta distribution, which is ideally suited to Bernoulli-type processes since it can assume a wide variety of skewed and symmetric shapes. Similarly, ξ denotes the precision of s_j. Respondents weight the probabilities as if the value of p_j were based on γ draws from a Bernoulli urn, and s_j were based on ξ draws, so that the total information content available is $\gamma + \xi$.[7] For the beta family of distributions, the posterior risk assessment q_j will be given by

$$q_j = \frac{\gamma p_j + \xi s_j}{\gamma + \xi} = \gamma' p_j + \xi' s_j \tag{1}$$

where $\gamma' = \gamma/(\gamma + \xi)$ and $\xi' = \xi/(\gamma + \xi)$. The γ' and ξ' terms consequently are the fractions of the total information accounted for by the baseline probability p_j and the new information s_j.

Individuals are, however, assumed to treat probabilities of 0 and 1 at face value. Certain events do not get filtered through some risk perception process. As a result, $q_j(s_j = 0) = 0$ and $q_j(s_j = 1) = 1$, as in Kahneman and Tversky's (1979) prospect theory and Viscusi's (1989) prospective reference theory. For both $j = 1, 2$, the value of p_j equals 15/10,000.

Case 2 is a variant of this learning formulation in which respondents do not restrict their beliefs to the information given to them in the survey. Instead, they approach the survey with some baseline prior beliefs drawn from their general knowledge and previous experiences. Thus they enter the survey with a risk perception r and associated precision ψ. Since the survey was only given to respondents who used the household chemical products, it is likely that respondents have some prior risk beliefs about these products.

The value of the posterior risk assessment in this instance will be

$$q_j = \frac{\psi r + \gamma p_j + \xi s_j}{\psi + \gamma + \xi} = \psi'' r + \gamma'' p_j + \xi'' s_j \tag{2}$$

where

$$\psi'' = \frac{\psi}{\psi + \gamma + \xi}, \quad \gamma'' = \frac{\gamma}{\psi + \gamma + \xi}, \quad \xi'' = \frac{\xi}{\psi + \gamma + \xi}.$$

The values of ψ'', γ'', and ξ'' are the proportions of the risk information accounted for by the consumer's prior beliefs, the base risk value, and the new risk value, respectively. The denominator used to determine the fraction of information from each source is larger than under case 1, as it now includes the informational content of prior risk beliefs as well.

The empirical formulations for cases 1 and 2 are summarized in table 2. The equation generating the posterior risk

sample. The survey was administered by a market research firm, and the sample characteristics closely parallel those of U.S. consumers nationally.

[6] The survey also included an experimental treatment in which the risk was increased. However, this treatment led to alarmist responses, which Viscusi et al. (1987) called "reference risk effects." Including these responses would add a shift term to the perception function to reflect the discontinuity in risk beliefs when risks are increased.

[7] The values of γ and ξ are assumed to be the same for each of the two product risks since the informational context in which the risks are presented in the survey is identical.

TABLE 2.—SUMMARY OF THEORETICAL MODELS

Parameters of Interest	Case 1 Consumers Use Information Contained Only in Survey	Case 2 Consumers Incorporate Prior Risk Beliefs
1. Posterior risk assessment q_j	$q_j = \gamma' p_j + \xi' s_j$	$q_j = \psi'' r_j + \gamma'' p_j + \xi'' s_j$
2. Equation to estimate	$q_j = \alpha + \beta s_j$	$q_j = \alpha + \beta s_j$
3. Interpretation of parameters α and β	$\alpha = \gamma' p_j$ $\beta = \xi'$	$\alpha = \psi'' r_j + \gamma'' p_j$ $\beta = \xi''$
4. Constant term/initial risk	$\alpha/p_j \equiv \hat{\alpha} = \gamma'$	$\alpha/p_j \equiv \hat{\alpha} = \psi'' r_j/p_j + \gamma''$

Definitions:
p_j = baseline risk (15/10,000) for all cases
s_j = new risk
r_j = prior risk perception
q_j = posterior risk perception

assessment, listed in row 1 of the table, is different in the two cases. Because the initial risk is $p_j = 15/10{,}000$ for both product hazards, the role of the baseline risk term in equations (1) and (2) can be captured through a constant term. For the case 2 model this constant term also reflects prior risk beliefs. The equation identified by the survey is therefore

$$q_j = \alpha + \beta s_j. \tag{3}$$

Thus for cases 1 and 2, our approach yields estimates of a constant term and a coefficient of the new risk information.

Item 3 in table 2 indicates how the differing ways prior information is incorporated into the posterior risk assessment necessitate a different interpretation for the parameters α and β across the two models. In case 1 the constant term α captures the influence of the initial risk information, and for case 2, the role of any prior risk beliefs. The new risk information coefficient β indicates the relative weight placed on the information for the new product, where the only difference between cases 1 and 2 is that for case 2 the relative weight on this information is with respect to a larger information base. Finally, as indicated in item 4 in table 2, the estimated constant term α divided by the initial risk (15/10,000) equals the relative weight γ' on the initial risk under case 1. For case 2 this value equals the relative weight γ'' plus a term reflecting the influence of prior risk beliefs. We will denote the ratio of α to 15/10,000 by $\hat{\alpha}$.

III. Estimation of Probabilities

Consumers faced with the new risk values presented in table 1 were asked what price premium they were willing to pay for the safer product. These responses establish an equality between the expected utility of the original product and the expected utility of the safer product, which will be used to estimate the nature of the probabilities revealed through this behavior.

In Evans and Viscusi (1991) we show that for this set of consumer data one cannot reject the hypothesis that these minor health losses are tantamount to monetary equivalents. Let L_i be the monetary equivalent loss for injury I, and WK ($K = 1, \ldots, 5$) be the respondent's willingness to pay for the formulation described in question K (see table 1). We present the formulation of the econometric model for case 1 (where the only information utilized by respondents is that given to them in the survey); the formulation for case 2 is analogous. Since $p_1 = p_2 = 15/10{,}000$, the initial risk level will be denoted by p. Finally, let N be the number of bottles of the product the respondent used per year. The survey structure ascertained the price change necessary to keep the subject on the same indifference curve and to continue to purchase the product. In the estimation, we assume that any income effects resulting from the small price changes involved in the survey are sufficiently small that quantity change effects can be ignored.

The survey ascertained the consumer's additional annual willingness to pay for the new safer product as opposed to the original product. The equality between the willingness to pay for injury reduction in annual expected injury costs for each of the five product variants is given by[8]

$$W1 = pNL_1 \tag{4a}$$

$$W2 = pNL_2 \tag{4b}$$

$$W3 = pN(L_1 + L_2) \tag{4c}$$

$$W4 = (p - q_j)N(L_1 + L_2) \tag{4d}$$

where q_j is evaluated at $s_j = 10/10{,}000$, and

$$W5 = (p - q_j)N(L_1 + L_2) \tag{4e}$$

where q_j is evaluated at $s_j = 5/10{,}000$.[9]

In each case, the expected injury cost is the product risk associated with the particular product, the number of bottles used, and the monetary equivalents loss. For product formulations 3, 4, and 5, there are two possible types of injuries,

[8] These equations are derived using first-order Taylor series expansions of arbitrary utility functions. The procedure is outlined in Evans and Viscusi (1991). These equations can also be obtained if one assumes risk-neutral utility. In Evans and Viscusi (1993) we derive expressions equivalent to equations (4) for a constant absolute risk aversion (exponential) utility function. In that model we demonstrate that the risk aversion parameter is extremely small, but is estimated imprecisely, and we cannot reject the hypothesis that consumers are risk neutral and treat the outcomes as monetary equivalents. Using estimates from linear, logarithmic, and exponential utility models, we also demonstrated in Viscusi and Evans (1990) that the parameters of the monetary loss equivalent function are invariant to the assumed form of utility.

[9] Because we assume that risk perceptions are accurate if stated risks are zero, risk perception parameters are absent from equations (4a) and (4b), and we can therefore identify the parameters for L_1 and L_2 using these two equations. Having identified these parameters, we then use the responses for the partial reduction in risks in equations (4d) and (4e) to identify $\psi'' r + \gamma'' p_j$ and ξ''. Because the risk perception variables are multiplicative constants in the equations of interest, we only have two equations from which to identify these parameters. Therefore we are unable to identify distinct r's for each injury.

whereas for products 1 and 2, there is only 1. The per-bottle risks are the same for products 1, 2, and 3, but the injury probability is less for products 4 and 5. Some of the valuation amounts are zero, as some respondents are not willing to pay extra for the additional safety improvement.[10] The presence of zero values is not a tobit situation since there is no reason to believe that respondents are being censored from giving negative values to what is an unambiguous product safety improvement.

As in Evans and Viscusi (1993), we allow for the possibility that the monetary loss equivalent value of injuries L_k ($k = 1, 2$) is a function of income, where

$$L_k = \phi_{0k} + \phi_{Yk}Y + \phi_{YYk}Y^2, \qquad k = 1, 2. \tag{5}$$

The econometric task is to incorporate the functional forms for q_j from equations (1) and (3) and L_k from equation (5) into the system of equations (4a)–(4e). Estimation of these five equations will consequently produce joint estimates of both the risk perception functions and individual utility functions. We estimate this set of equations using nonlinear iterative seemingly unrelated regressions (ITNSUR).[11] The iterative aspect arises as estimates of the equation system and the associated covariance terms are obtained, and the equations are reestimated until stable parameter estimates are obtained. The only parameters to be estimated are the risk perception function parameters from equations (1) and (3) and the loss function parameters from equation (5).

Table 3 presents the estimation results for the toilet bowl cleaner sample and the insecticide sample. The upper panel presents the perception parameters, and the lower panel presents the utility function parameter estimates. The interpretation of the results is most straightforward using case 1, in which the risk beliefs are based only on the survey information. The estimation procedure yields values of β and of $\alpha/(15/10{,}000)$, or $\hat{\alpha}$. The value of β equals the weight on the new risk information for both cases 1 and 2. As indicated in table 2, the coefficient $\hat{\alpha}$ corresponds to the weight γ' on the initial risk p (case 1) and a more complicated expression involving γ'' for case 2. In both samples, these coefficients are positive and significantly different from both 0 and 1 (95% confidence interval).

Consider the implications for the case 1 model. One can reject the following extreme hypotheses: the new experimental information regarding the altered product is taken at face value ($\gamma' = 0, \beta = 1$, or the survey provides perfect information), respondents ignore the experimental information ($\gamma' = 0, \beta = 0$), and respondents only weight the initial risk and do not believe that the safer product variant reduces the risk ($\gamma' = 1, \beta = 0$). If the set of information influencing decisions is restricted to what is provided in the survey, the estimates have definitive implications with respect to three principal learning hypotheses.

For the case 2 model, the value of $\hat{\alpha}$ is $\psi''r/(15/10{,}000) + \gamma''$. This term captures both the underlying risk beliefs and the role of the initial product risk information. Based on the estimates of $\hat{\alpha} = 0.101$ (toilet bowl cleaner) and $\hat{\alpha} = 0.438$ (insecticide), it cannot be the case that $\psi''r = 0$ and $\gamma'' = 0$, but it is possible that one of them is. It is also clear that since $\beta = 0.693$ (toilet bowl cleaner) and 0.280 (insecticide), $\xi'' \neq 1.0$, so that the perfect information case can be ruled out. Individuals do not act as if all of the information they use in evaluating the new product had the stated risk level associated with it.

Overall, the results are consistent with an intermediate model in which both the initial and the modified risk values enter. For both the case 1 and the case 2 models, the results are consistent with a mixed weighting scheme that might, for example, occur in a Bayesian learning context in which both pieces of product information enter. For the case 1 model, the proportional weight on the initial risk information is 0.10 for the toilet bowl cleaner and 0.44 for the insecticide, and the weights on the new risk information are 0.69 for the toilet bowl cleaner and 0.28 for the insecticide. These results suggest that respondents believe the reduced risk information about the toilet bowl cleaner is relatively credible, whereas the insecticide risk perception amounts are more difficult to alter, perhaps because respondents believe this product is inherently risky.

Table 3.—Nonlinear ITSUR of Consumer Product Risk Model, Parameter Estimates, and Asymptotic Standard Errors

	Toilet Bowl Cleaner Sample	Insecticide Sample
Perception parameters		
$\hat{\alpha}$	0.101[b]	0.438[c]
	(0.052)	(0.037)
β	0.693[c]	0.280[c]
	(0.069)	(0.055)
Utility function parameters		
ϕ_{01}	392.62[c]	850.80[c]
	(56.52)	(373.16)
ϕ_{Y1}	0.009[c]	0.028[b]
	(0.003)	(0.015)
ϕ_{YY1}	−1.1E-3	−2.5E-3[b]
	(4.0E-4)	(1.3E-3)
L_1[a]	563.67[c]	1559.48[c]
	(23.92)	(92.63)
ϕ_{02}	193.49	550.22[b]
	(123.02)	(318.54)
ϕ_{Y2}	0.026[c]	0.029[c]
	(0.007)	(0.013)
ϕ_{YY2}	−2.9E-3[c]	−2.4E-3[c]
	(8.8E-4)	(1.1E-3)
L_2[a]	698.94[c]	1293.99[c]
	(53.55)	(77.59)

Notes: [a] Loss values are evaluated at sample mean for income.
[b] Coefficients are statistically significant at the 95% confidence level, one-tailed test.
[c] Coefficients are statistically significant at the 95% confidence level, two-tailed test.

[10] For example, in the case of *W3*, where both risks decrease to zero, 5.9% of the toilet bowl subjects and 13.9% of the insecticide respondents give zero values.

[11] See Gallant (1975, 1986) for a description of the properties of this procedure.

For the case 1 model, the values of $\hat{\alpha}$ and β represent the proportional weights on each type of risk information, which theoretically should sum to 1.0 in a Bayesian learning model (see equation (1)). For the toilet bowl cleaner sample, $\hat{\alpha} + \beta = 0.794$, with a standard error of 0.025, and for the insecticide sample $\hat{\alpha} + \beta = 0.719$, with a standard error of 0.034. In each instance, the results are not consistent with the Bayesian learning model in which no prior risk information enters since the sum of the weights is significantly below 1.0.

The behavior implied by the case 1 results is similar in general character to what Kahneman and Tversky (1979) have termed "subcertainty," that is, the sum of the perceived probabilities for events that should have a combined probability equal to 1.0 is less than this amount. The estimates of the revealed risk perception relationships provide formal tests of these relationships against perfect information and Bayesian learning reference points, with implications suggesting that there are perceptional biases that may not be consistent with the usual rational economic models of behavior. As will be seen in the discussion of case 2, prior risk beliefs must play a role to avoid this anomaly.

For the case 2 model one cannot reject the hypothesis that the results are consistent with a Bayesian learning approach. In the case 2 analysis, the estimated value $\hat{\alpha}$ corresponds to the value of $\psi''r/(15/10{,}000) + \gamma''$. In a Bayesian learning framework, the sum of $\psi'' + \gamma'' + \xi''$ should equal 1.0, but the empirical analysis makes it possible to calculate an expression that is somewhat different, as $\hat{\alpha} + \beta$ equals $[\psi''r/(15/10{,}000)] + \gamma'' + \xi''$. The role of unobserved prior risk beliefs is influential. If the Bayesian assumptions are met, this expression will have a value below 1.0 if $r < 15/10{,}000$, equal to 1.0 if $r = 15/10{,}000$, and above 1.0 if $r > 15/10{,}000$.

To see how different implications from adherence to a rational Bayesian model can arise, consider the extreme case in which the value of $r = 0$. Then the results imply that $\gamma/(\psi + \gamma + \xi)$ equals the estimated value of $\hat{\alpha}$ in table 2 and $\xi/(\psi + \gamma + \xi)$ equals the estimated value of β in table 3. The Bayesian assumption that the relative informational weights (ψ'', γ'', and ξ'') sum to 1 will be satisfied if $\psi'' = \psi/(\psi + \gamma + \xi)$ equals 0.21 for the toilet bowl cleaner sample and 0.28 for the insecticide sample. The relative weight ψ'' on the prior risk level r must satisfy minimum requirements when $r = 0$. If such conditions are met, the results may be consistent with a Bayesian model in which subjects bring prior beliefs about the product to the study, in addition to acquiring risk information based on the survey.[12]

The nature of the effect on risk perceptions is of considerable interest as well. Perceptions are never so extreme as to fall outside of [0, 1]. Instead, the behavioral probabilities compress the values of the stated risk levels in the survey, leading to what we term the "probability compression effect."

Figure 1 illustrates the nature of the compression relationships. In each case, respondents act as if there were some positive risk of the product that should be taken into account, and they then increase these risk perceptions linearly as the value of s_j increases. Each of these lines is flatter than the 45° line that would prevail if stated probabilities equaled behavioral probabilities.

The effect of perceptional biases on the valuation responses differs according to the distribution of these perceptions for the particular sample. Table 4 reports the additional amount per year that respondents were willing to spend for products that has a decreased per-bottle risk of 5/10,000. The first column in table 4 presents the actual survey responses, and the second column presents the median increase in expenses that subjects would be willing to incur if the risk perceptions were adjusted for their perceptional bias. In the case of toilet bowl cleaner, the adjustment for perceptional bias is not statistically significant, but for insecticide the willingness to pay for the greater safety is significantly smaller.

Willingness to pay for changes in risk consequently may be distorted by the presence of these inadequacies in risk perception. This phenomenon is more than of academic interest, since it has implications not only for estimated risk–money tradeoffs but also for the degree and character of market failure. As the results in table 4 indicate, the extent of this influence may differ considerably depending on the particular risk context.

IV. Implications

The empirical innovation of this paper was to extend the analysis in Evans and Viscusi (1991) to jointly estimate the revealed probabilities and utility functions. The data requirements for these estimates are fairly modest, as all that is needed is information that equates an individual's expected utility for two or more situations. The context considered focused on consumer product safety, but the results clearly have general applicability.

This approach enables one to identify the role of perceptional biases in apparent violations of the expected utility model. In each case it was possible to explore explicitly whether the results were consistent with a Bayesian formulation. Although the learning process is similar in many respects to a Bayesian learning process, it fell short if attention focuses on models in which the only information that matters is presented in the survey. The proportional information weights summed to less than their Bayesian value of 1.0. This suggests that either subjects are Bayesian who bring to an experimental study prior risk information that plays a substantial role or that the Bayesian model does not hold.[13]

[12] This hypothesis is consistent with the prospective reference formulation in Viscusi (1989, 1992).

[13] There could be other explanations as well. There could be specification errors due to the model's simplifying assumptions or a bias on the survey results that is not reflected in actual behavior.

FIGURE 1.—RELATIONSHIP BETWEEN BEHAVIORAL AND STATED PROBABILITIES

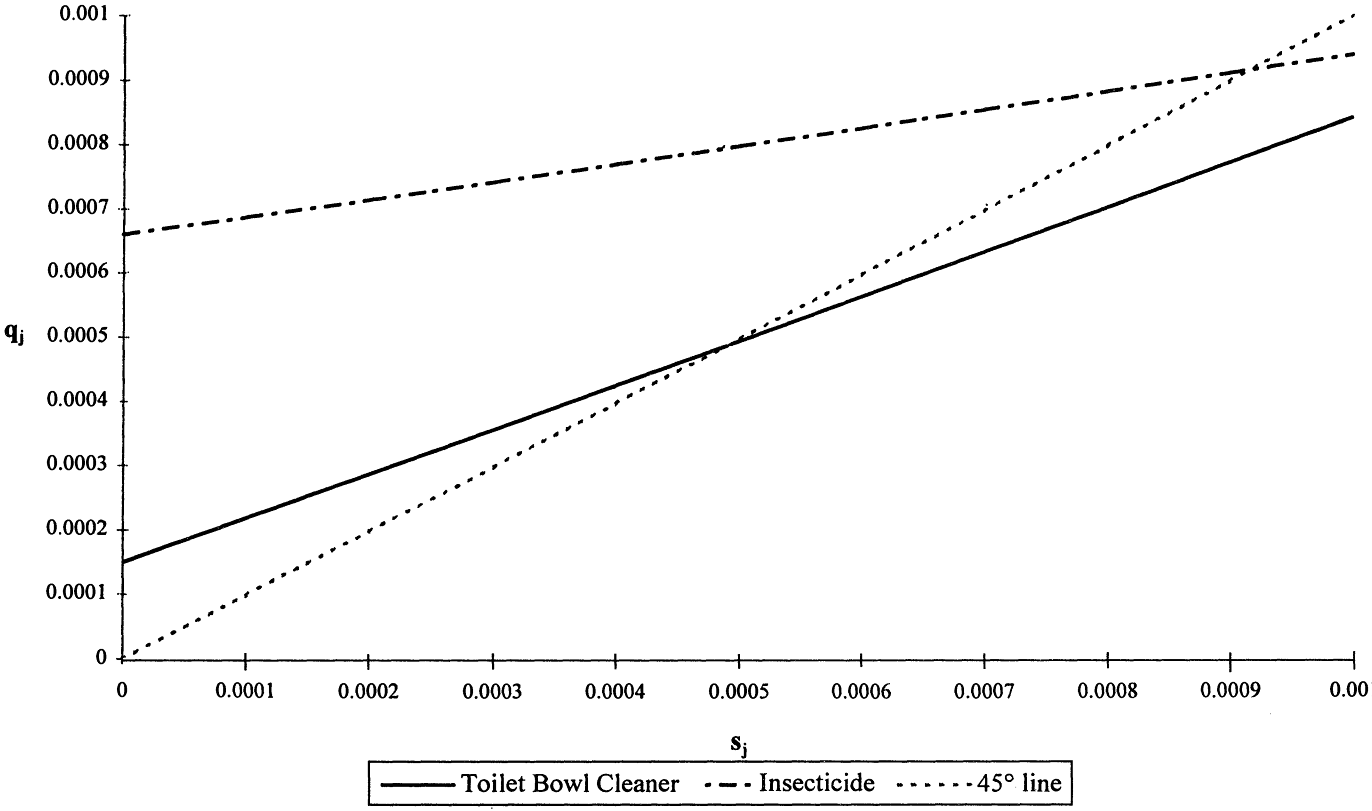

TABLE 4.—IMPACT OF PERCEPTIONAL BIAS ON SURVEY RESPONSES

Sample	Predicted Median Increase (Std. Error) in Yearly Expenses for a Decrease in Per-Bottle Risk to 5/10,000: Assuming Stated Risk Is Accurate	Stated Risk Is Adjusted for Perceptional Bias
Toilet bowl cleaner	\$ 8.32 (0.37)	\$ 8.34 (1.06)
Insecticide	\$ 3.92 (0.22)	\$ 2.75 (0.34)

Notes: Using parameter estimates from table 3, predicted values for *W5* in equation (4e) are calculated for each respondent. In column 1 we assume consumers believe the stated risk q_j = 5/10,000 is accurate. In column 2 we assume the stated risk is used in formulating the perceived risk as described in equation (3). The differences in the toilet bowl cleaner median values are not statistically significant where the insecticide value differences are statistically significant.

There is also an apparent floor on behavioral probabilities. These values increase less than proportionally with either the stated or the assessed probabilities.

REFERENCES

Combs, Barbara, and Paul Slovic, "Causes of Death: Biased Newspaper Coverage and Biased Judgments," *Journalism Quarterly* 56 (1974), 837–843, 849.

Evans, William, and W. Kip Viscusi, "Estimation of State-Dependent Utility Functions Using Survey Data," this REVIEW 73:1 (1991), 94–104.

——— "Income Effects and the Value of Health," *Journal of Human Resources* 28:3 (1993) 497–518.

Fischhoff, Baruch, Sara Lichtenstein, Paul Slovic, Stephen L. Derby, and Ralph L. Keeney, *Acceptable Risk* (Cambridge, UK: Cambridge University Press, 1981).

Gallant, A. Ronald, "Seemingly Unrelated Nonlinear Regressions," *American Statistician* 3 (1975), 35–50.

——— *Nonlinear Statistical Models* (New York: Wiley, 1986).

Kahneman, Daniel, and Amos Tversky, "Prospect Theory: An Analysis of Decision under Risk," *Econometrica* 47 (1979), 263–291.

Keeney, Ralph, and Howard Raiffa, *Decisions with Multiple Objectives: Preferences and Value Tradeoffs* (New York: Wiley, 1976).

Kleindorfer, Paul R., Howard C. Kunreuther, and Paul J. Schoemaker, *Decision Sciences: An Integrative Perspective* (Cambridge, UK: Cambridge University Press, 1993).

Kunreuther, Howard, Ralph Ginsberg, Louis Miller, Philip Sagi, Paul Slovic, Bradley Borkan, and Norman Katz, *Disaster Insurance Protection: Public Policy Lessons* (New York: Wiley, 1978).

Lichtenstein, Sara, Paul Slovic, Baruch Fischhoff, Ulaark Layman, and Barbara Combs, "Judged Frequency of Lethal Events," *Journal of Experimental Psychology* 4 (1978), 551–578.

Machina, Mark J., "Perception of Risk," *Science* 236 (1987), 537–543.

Magat, Wesley A., and W. Kip Viscusi, *Informational Approaches to Regulation* (Cambridge, MA: MIT Press, 1992).

Raiffa, Howard, *Decision Analysis* (Reading, MA: Addison-Wesley, 1968).

Viscusi, W. Kip, "Prospective Reference Theory: Toward an Explanation of the Paradoxes," *Journal of Risk and Uncertainty* 2:3 (1989), 235–264.

——— *Fatal Tradeoffs: Public and Private Responsibilities for Risk* (New York: Oxford University Press, 1992).

Viscusi, W. Kip, and William Evans, "Utility Functions that Depend on Health Status: Estimates and Economic Implications," *American Economic Review* 80:2 (1990), 353–374.

Viscusi, W. Kip, Wesley A. Magat, and Joel Huber, "An Investigation of the Rationality of Consumer Valuations of Multiple Health Risks," *Rand Journal of Economics* 18:4 (1987), 465–479.